

Test The Fingerprinting Method For Climate Signal Detection Using Solar Reflectance Averaged In Large Time And Space Scales

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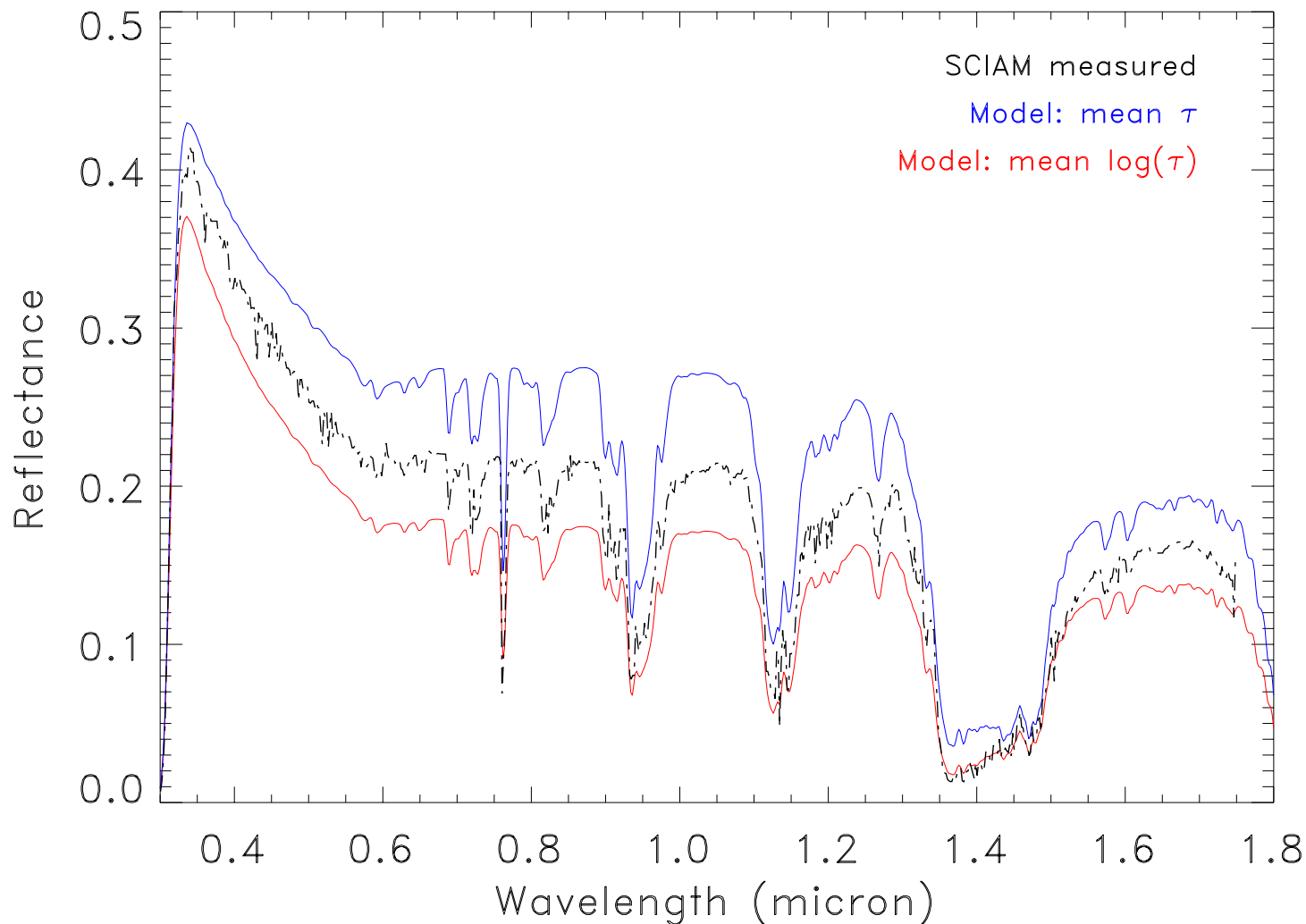
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The mean spectral reflectance over large space/time scales is required for many climate studies (e.g., the attribution of climate change signal and the perturbation analysis of a climate system); CLARREO has proposed to use it as the climate benchmark spectrum.

This mean spectral reflectance can be derived from satellite measurements or from model simulation, but measured RS spectrum over globe is limited.

Spaceborne sensors have measured the atmospheric and surface properties over globe for decades and have accumulated a large volume of instantaneous measurement data that could be used to simulate the spectral radiation over long time and globe. However, it is computationally too expensive to simulate the mean spectral radiance over large climate domains by explicit RT computations at the satellite footprint scales.

A simplifying approach for efficient RT computation has to be developed to use the instantaneous satellite data.

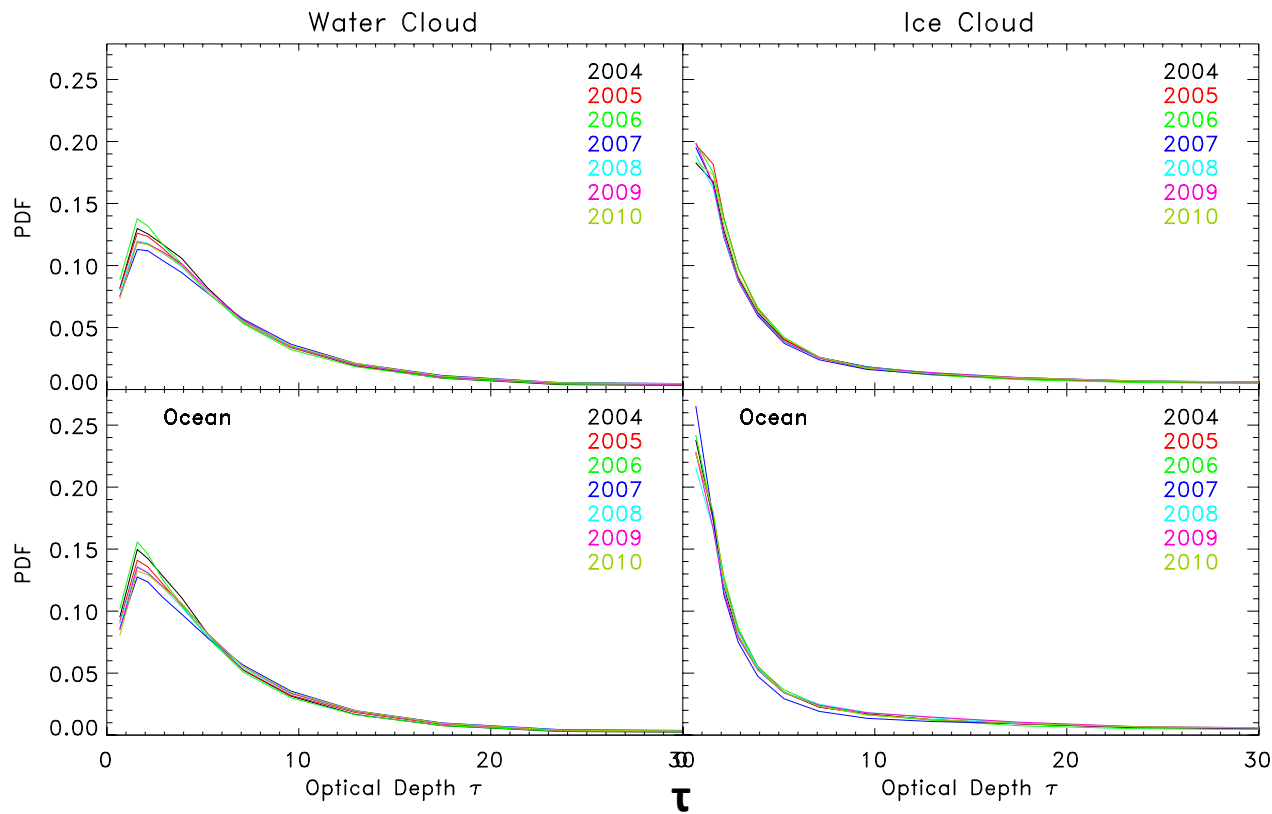


Inputs: MODIS clouds, aerosol, GOES5 water vapor in CERES SSF; SMOBA ozone; SeaWiFS Chl.

An example of model-observation comparison of spectral reflectance. This example is for one zone (30S-35S) in the January of 2006. (ocean only)

Input data are averaged in each month: 5 x 5 deg grid → 5 deg latitude zones.

Model computation in each zone: land, ocean → clear, cloudy → ice and water.



Example of
cloud τ PDF
In one zone

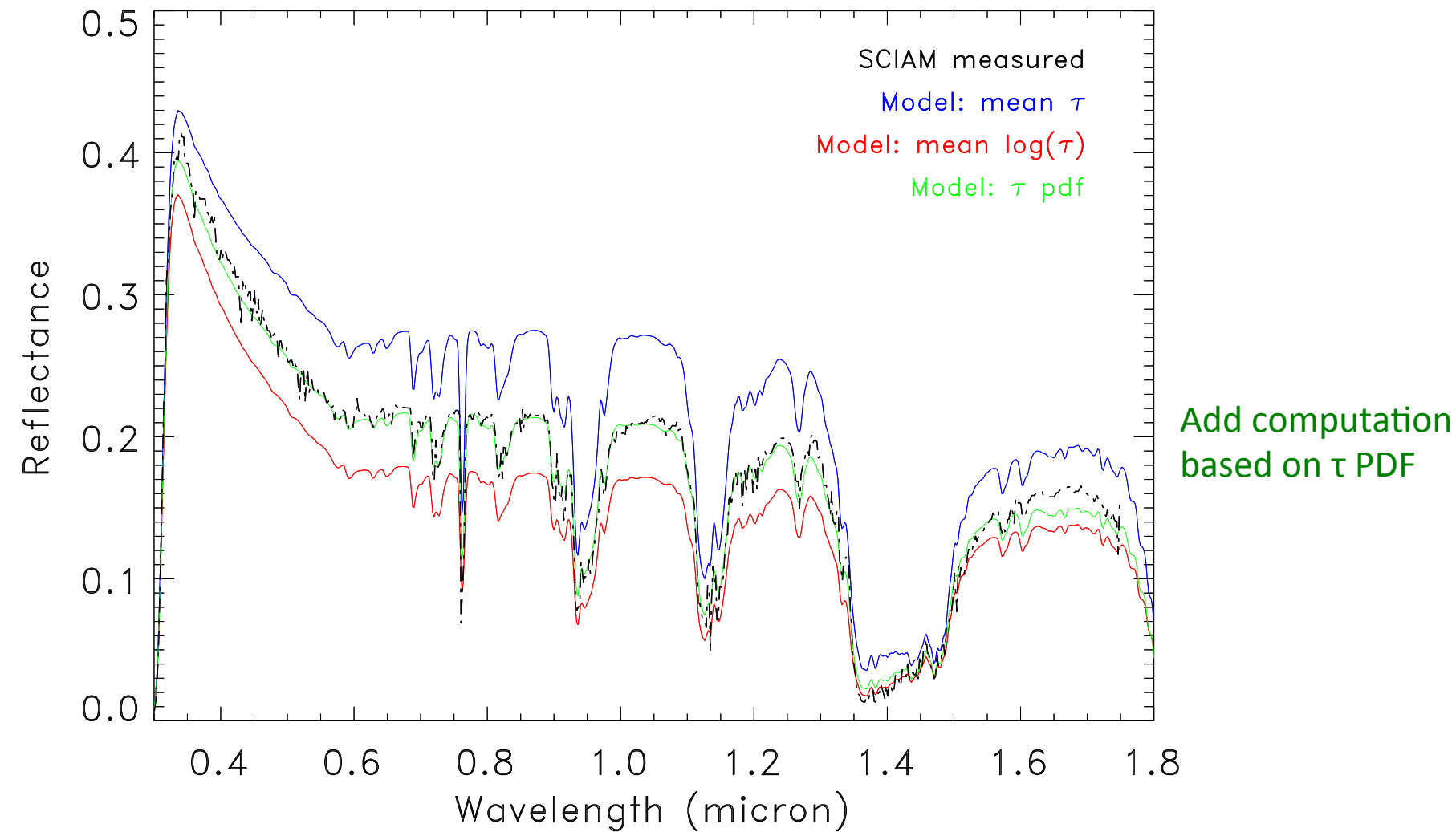
An example of the probability distribution function (PDF) of the instantaneous cloud τ in one latitude zone for months of April. A different color in each panel represents a different year.

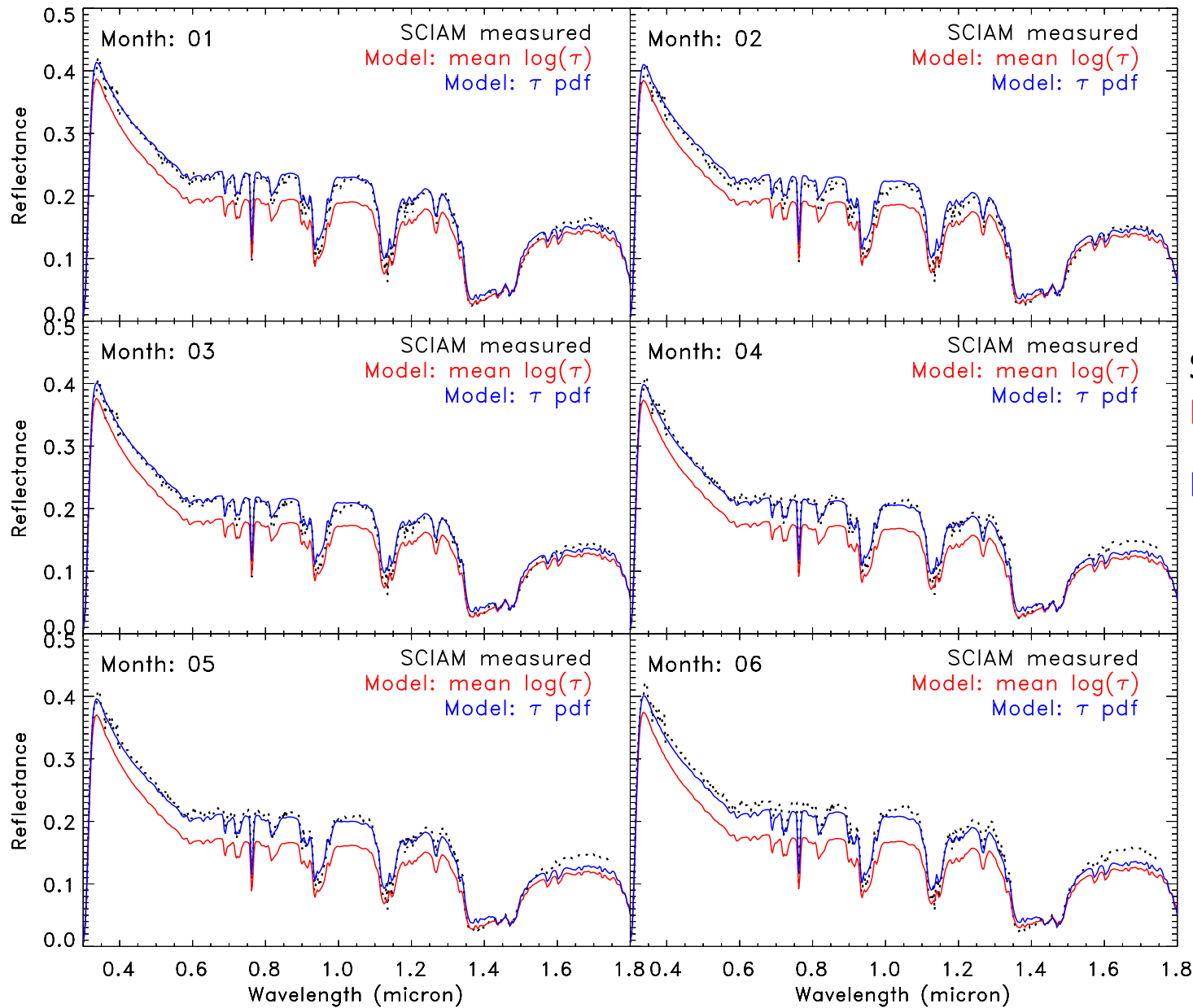
Based on the cloud τ PDF, we partition the cloudy footprints in each zone into a number of bins to account for the wide variation of cloud properties in different satellite footprints.

The PDF approach essentially organizes or groups the large number of satellite instantaneous measurements according to the τ value, so that those footprints with similar τ and other atmospheric/surface properties are treated once, rather than footprint by footprint, in the RT modeling. Therefore, the computation time is reduced significantly compared with the computation footprint by footprint.

Results for every τ bin are then summed and averaged to obtain the mean radiance with the weight in each bin equal to the integral of the PDF in the bin.

Jin, Z. et al. (2013), An efficient and effective method to simulate the earth spectral reflectance over large temporal and spatial scales, ***Geophys. Res. Lett.***, 40, 374–379, doi: 10.1002/grl.50116.



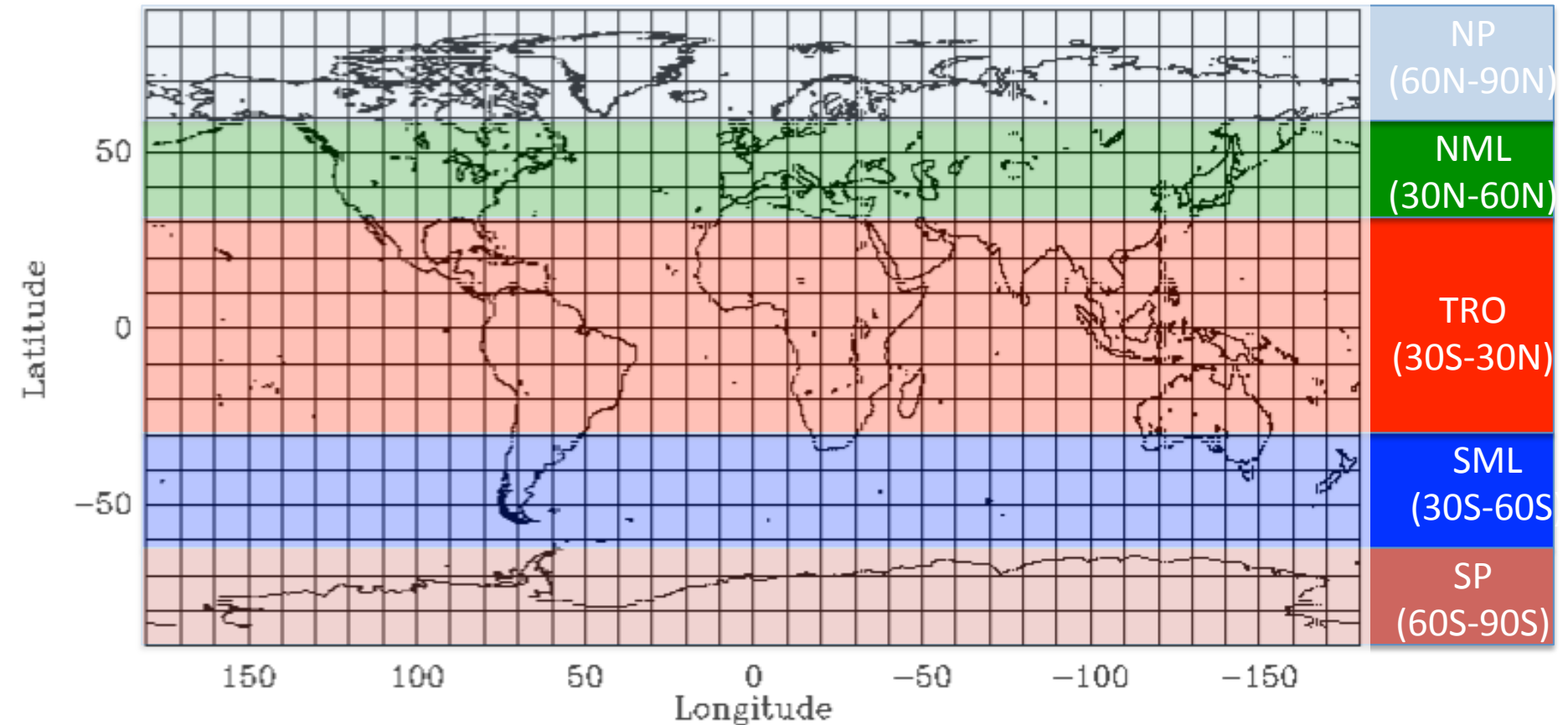


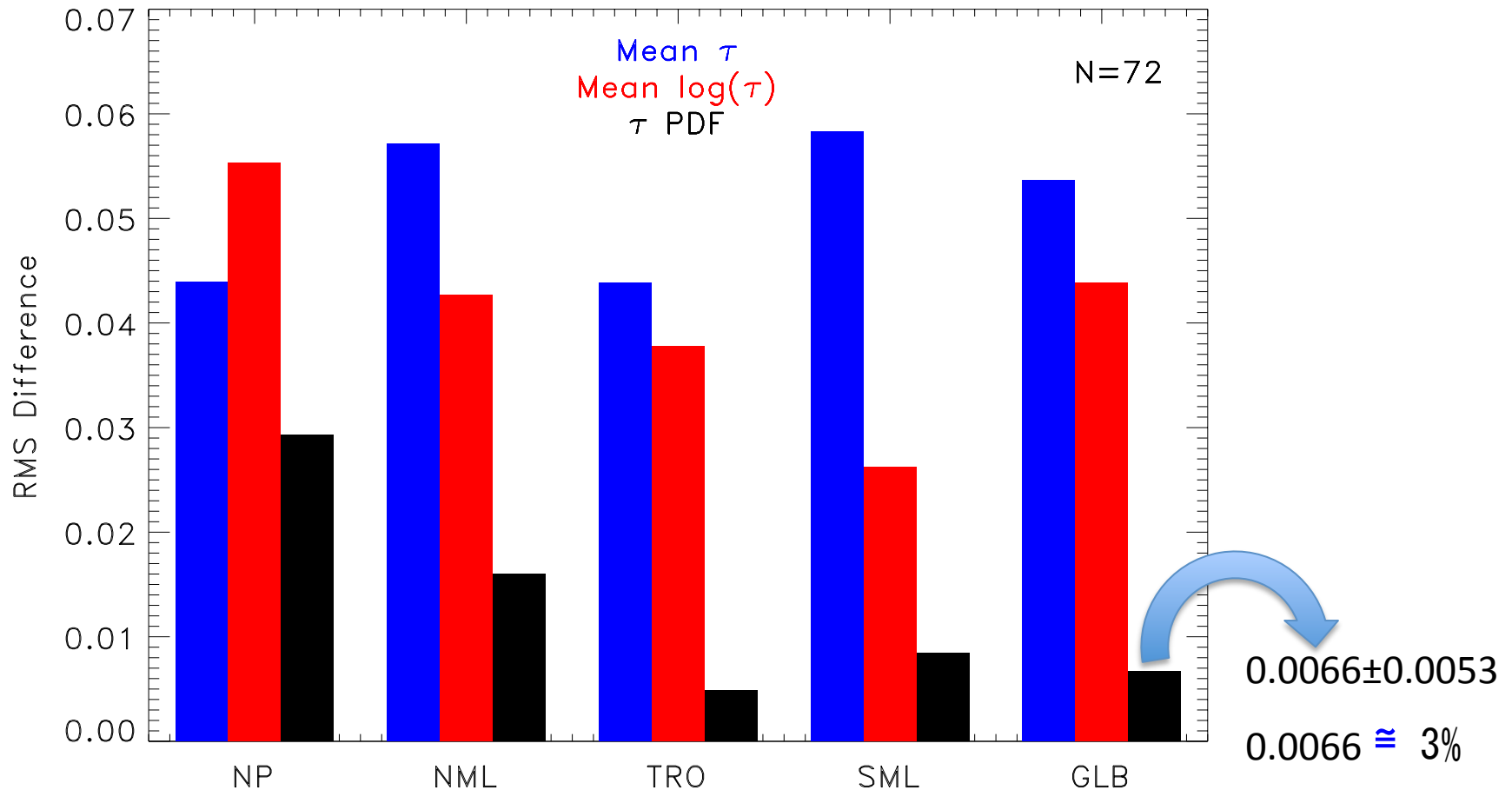
SCIAM measured
Model with mean τ
Model with τ PDF

Comparison of observed and calculated monthly and globally averaged spectral nadir reflectance (ocean only).

The PDF algorithm is tested in the five large latitude regions.

Five latitude regions





The RMS model discrepancy in the monthly mean reflectance in the five latitude regions (based on the results in the 72 months from 2004 to 2009). Each color bar represents a RMS error for a different modeling approach.

Application to Solar Fingerprinting Test

The climate change fingerprinting is to attribute the large spatiotemporal averaged spectral variation to different climate variables:

$$\Delta R = K \Delta X + e \quad (1a)$$

$$\Delta R_i = \sum_{j=1}^{n_x} K_{ij} \Delta X_j + e_j \quad (1b)$$

$$K_{ij} = \frac{\partial R_i}{\partial x_j}; \quad i=1,2,\dots,n_w; \quad j=1,2,\dots,n_x \quad (1c)$$

ΔR Reflectance change signal (spectral difference between two climate states)

K Kernel matrix (fingerprints), **has to be generated from RT modeling**

ΔX Climate variable changes to be retrieved

e Errors or residuals that cannot be explained by fingerprints

Solution by least squares estimation (LSE): $\Delta X = (K^T K)^{-1} K^T \Delta R$ (2a)

Solution by optimal detection: $\Delta X = (K^T E^{-1} K)^{-1} K^T E^{-1} \Delta R$ (2b)

The formulation for fingerprinting retrieval here is similar to those used in many conventional retrieval methods applied to instantaneous satellite data. However, the fingerprinting retrieval differs from the traditional remote sensing retrieval in that

- 1) It uses the average-then-retrieval approach and thus is associated with the averaged quantities over large spatiotemporal scales instead of the local or instantaneous values.
- 2) It is for the difference (ΔR and ΔX) between two climate states instead of the absolute value (R and X).

The linear expression above implies that ΔR and ΔX have to small to maintain sufficient linearity.

We use model-simulated data to test the concept of fingerprinting attribution. Model input parameters:

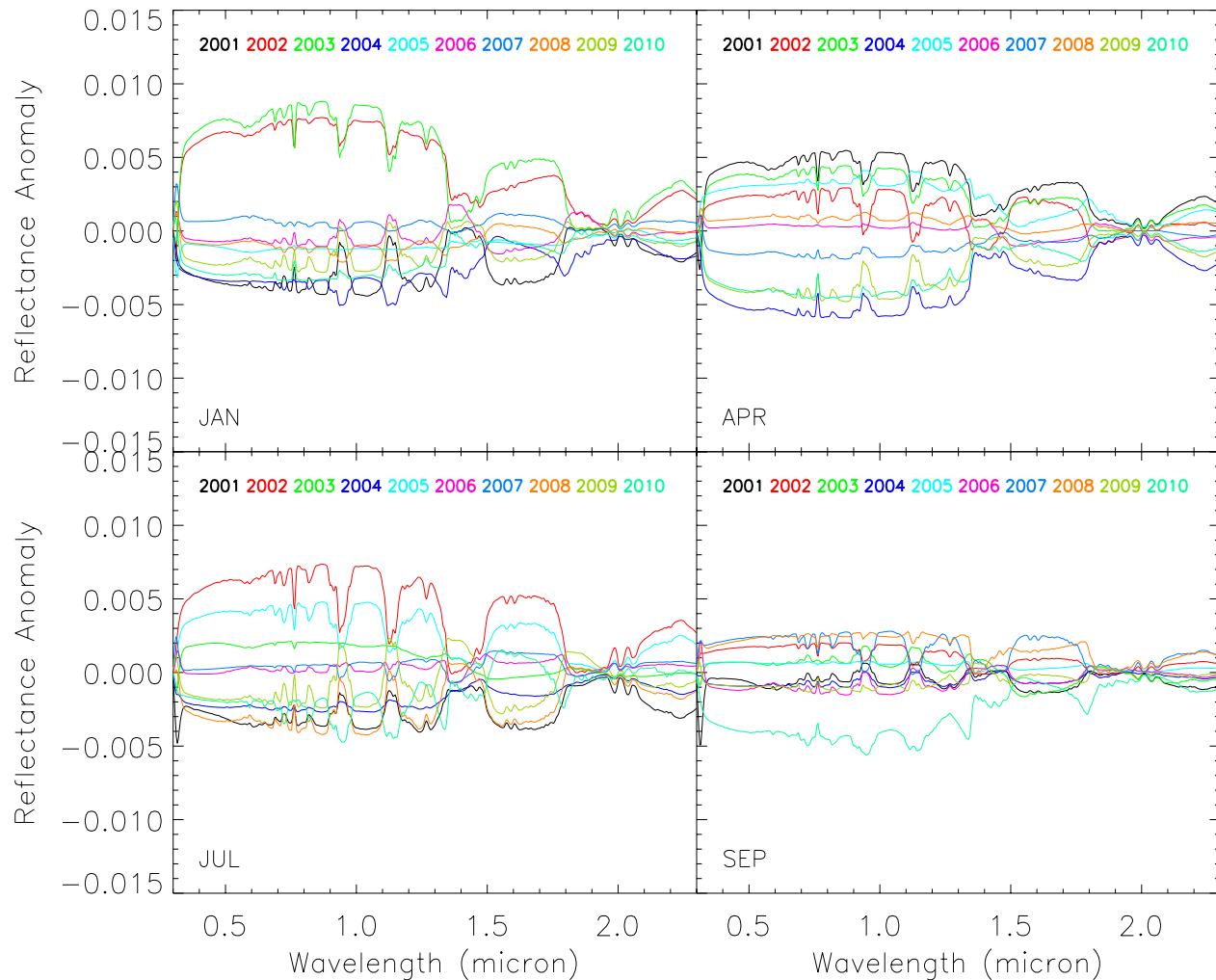
- ✓ 10 years (2001-2010) of CERES SSF data from NASA Terra satellite ;
- ✓ aerosol and cloud properties (optical depth, particle size, phase, and height) retrieved from MODIS;
- ✓ column water vapor and surface wind data from GEOS5-MERRA reanalysis;
- ✓ ozone data from SMOBA;
- ✓ ocean chlorophyll concentration from SeaWiFS.

Input these parameters to the combined COART-MODTRAN model, we generated the spectral kernels and a time series (10 years) of monthly mean reflectance spectra (320-2300nm, 4nm resolution) to retrieve the interannual changes in the 11 relevant climate parameters:

PW, AOD, O_3

and

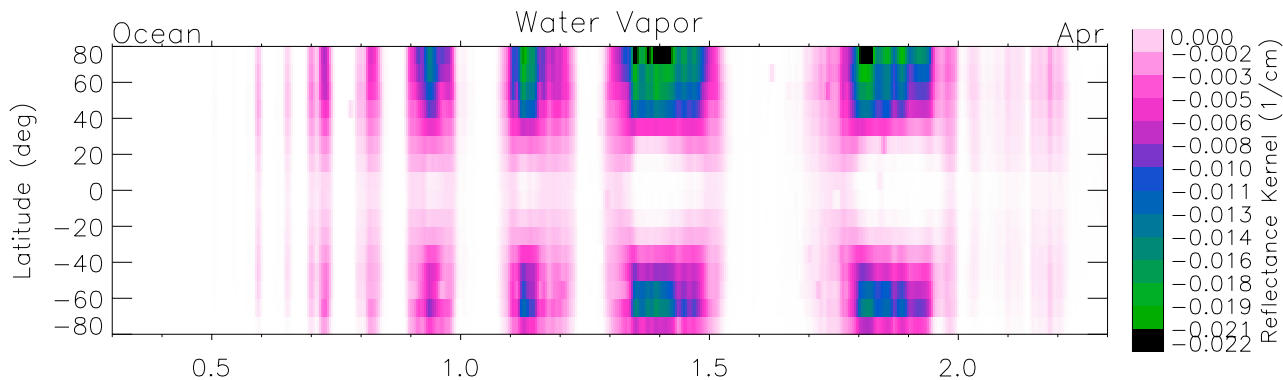
τ , F_c , H_t , Re for water and ice clouds, respectively.



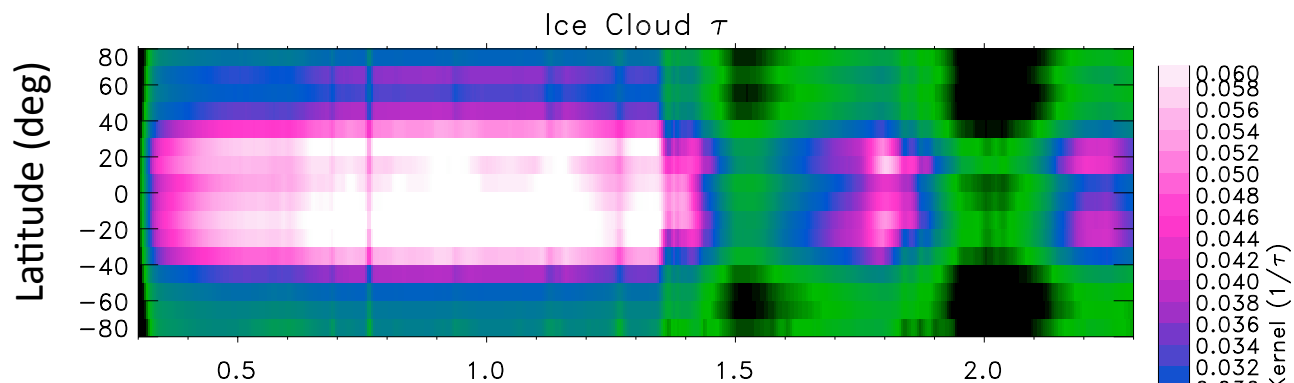
An example of the model-simulated monthly and global mean reflectance anomalies (ΔR) in the four months. In each panel, each color is for a different year.

ΔR is indeed small: typically less than $\pm 3\%$ of the mean reflectance

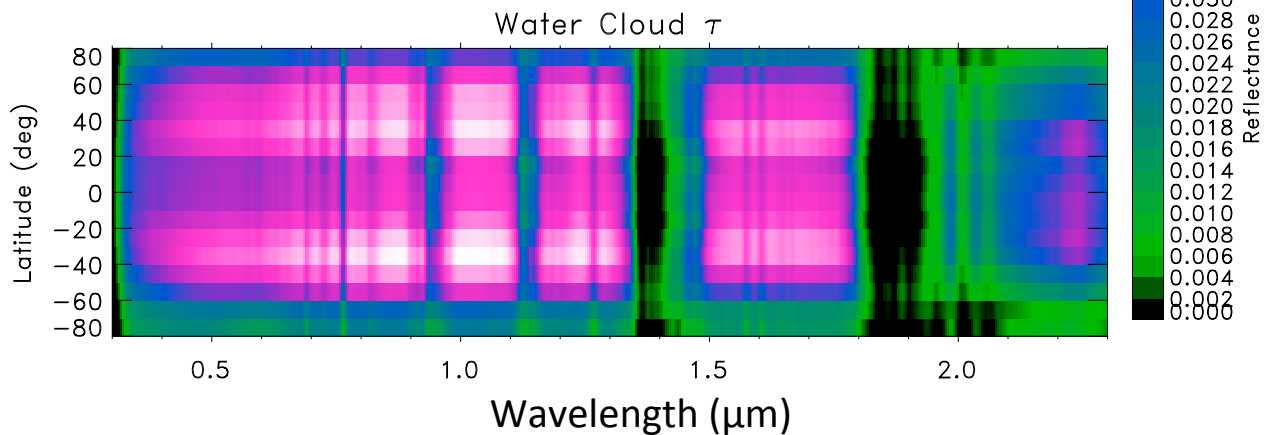
PW



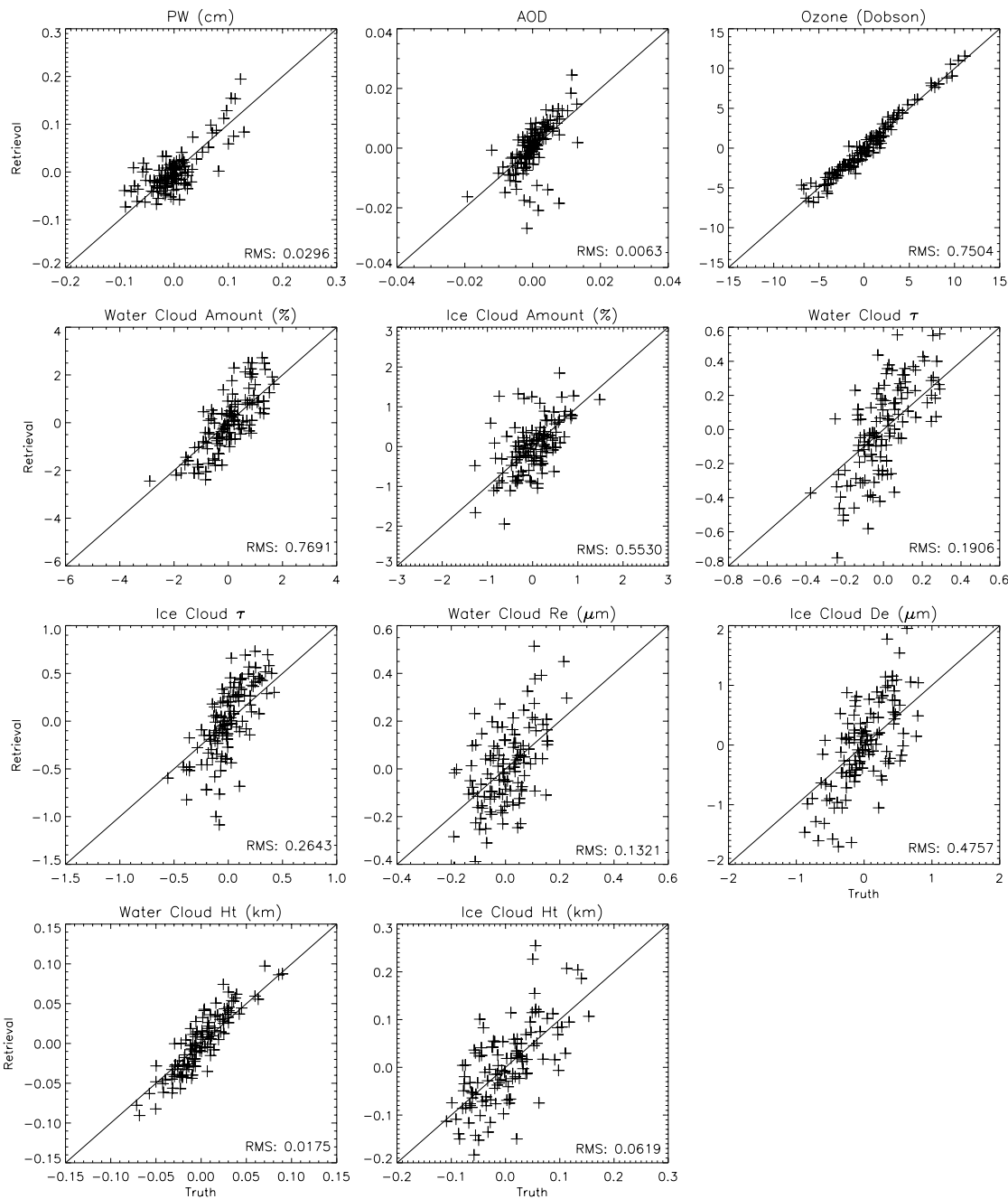
τ_{ice}



τ_{wat}



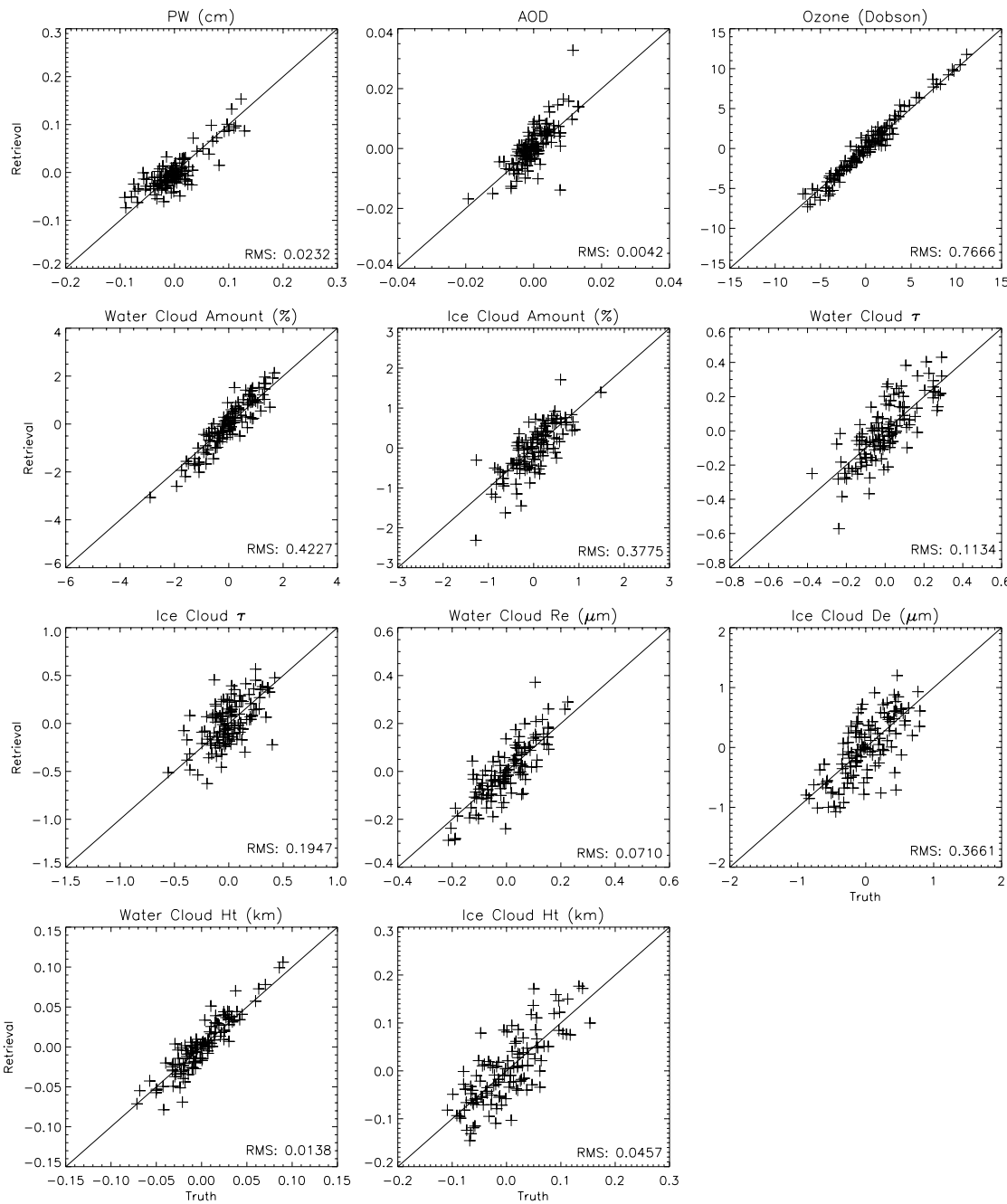
An example of solar spectral reflectance kernels.



Comparison between the fingerprinting retrieval and the observational truth for the monthly global mean anomaly.

Each panel is for a different climate parameter (11 total).

The nonlinear error in kernels is not considered in the retrieval.



Same retrieval as above, but
the nonlinear error in kernels is
considered.

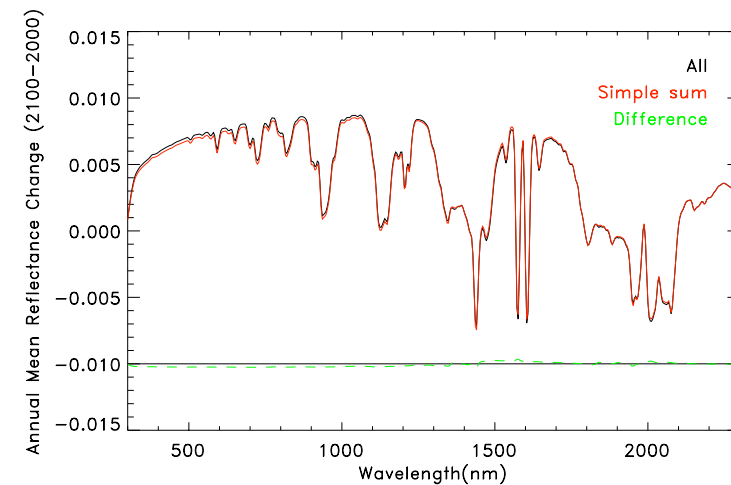
Two nonlinear error sources:

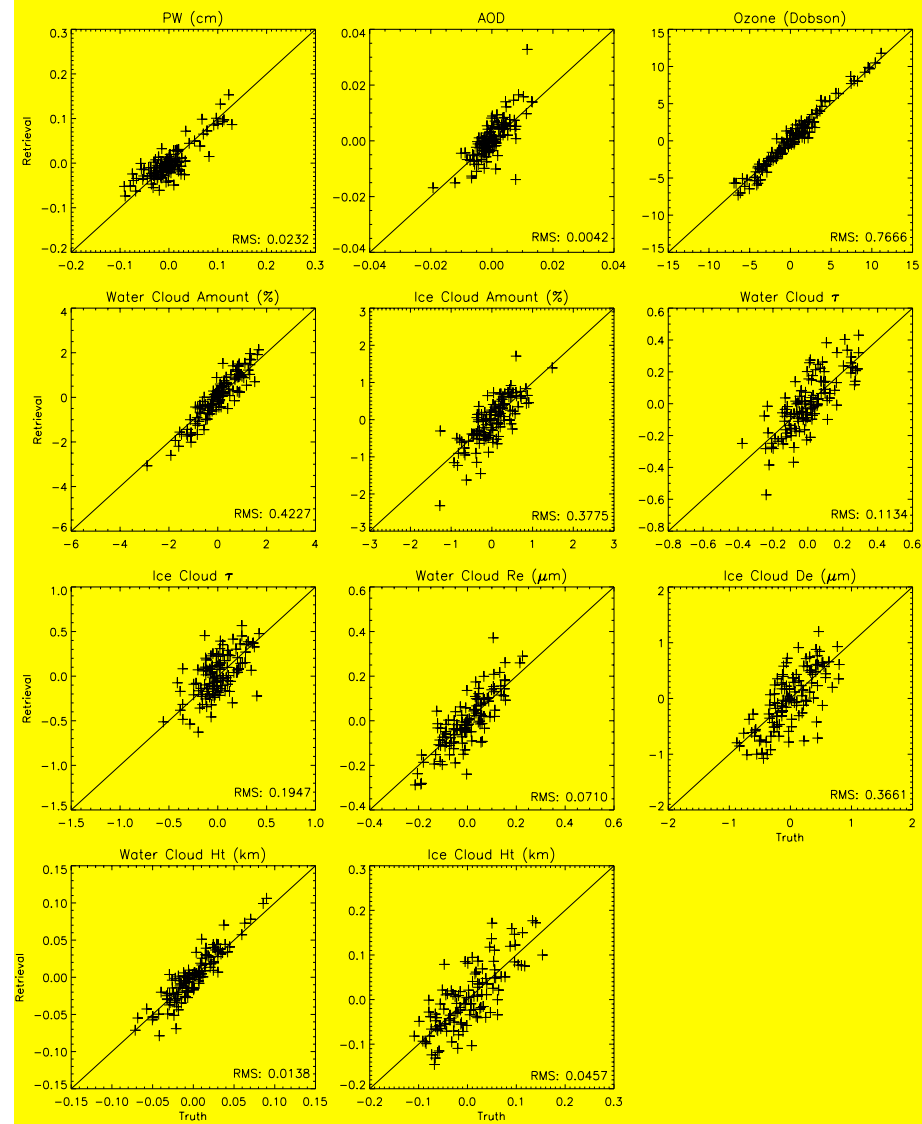
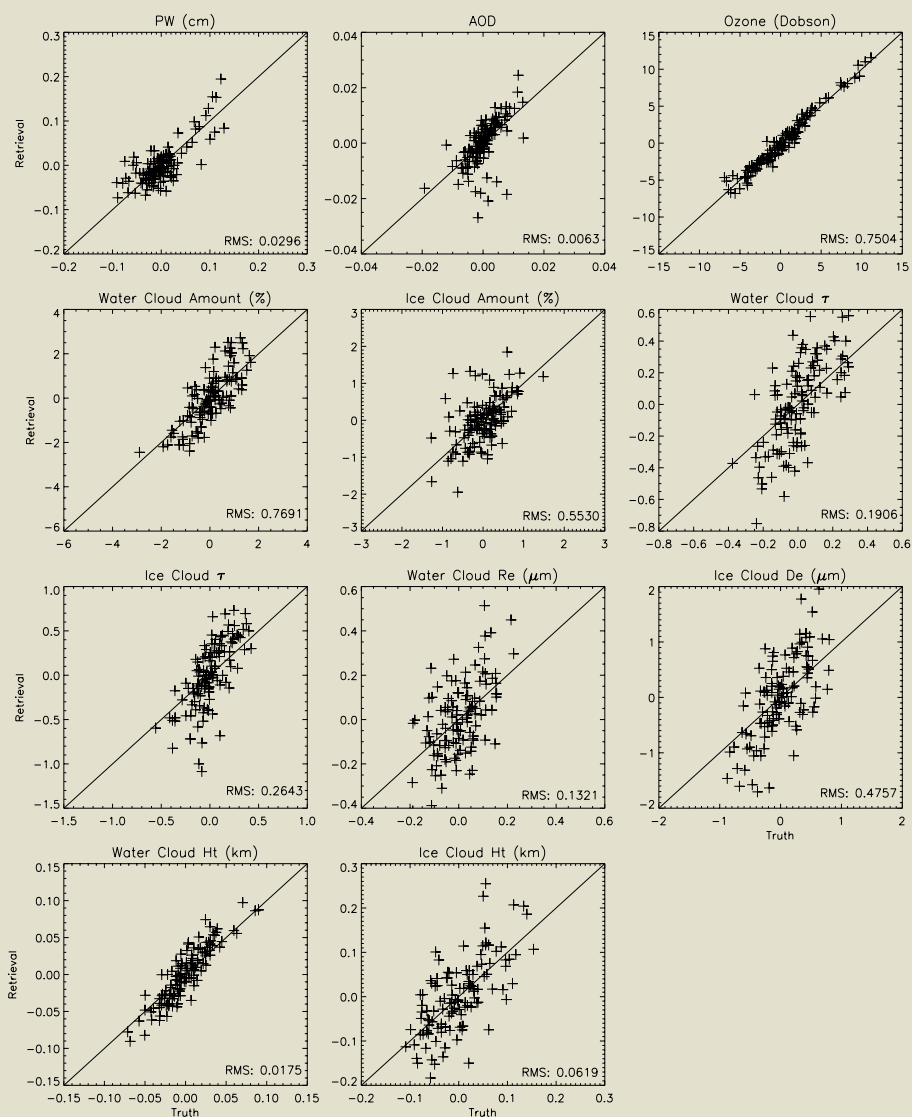
1). nonlinear radiative response :

$$\int_{x_0}^{x_0+\Delta x} K(x) dx \neq K(x_0) \Delta x$$

2). radiative interactions:

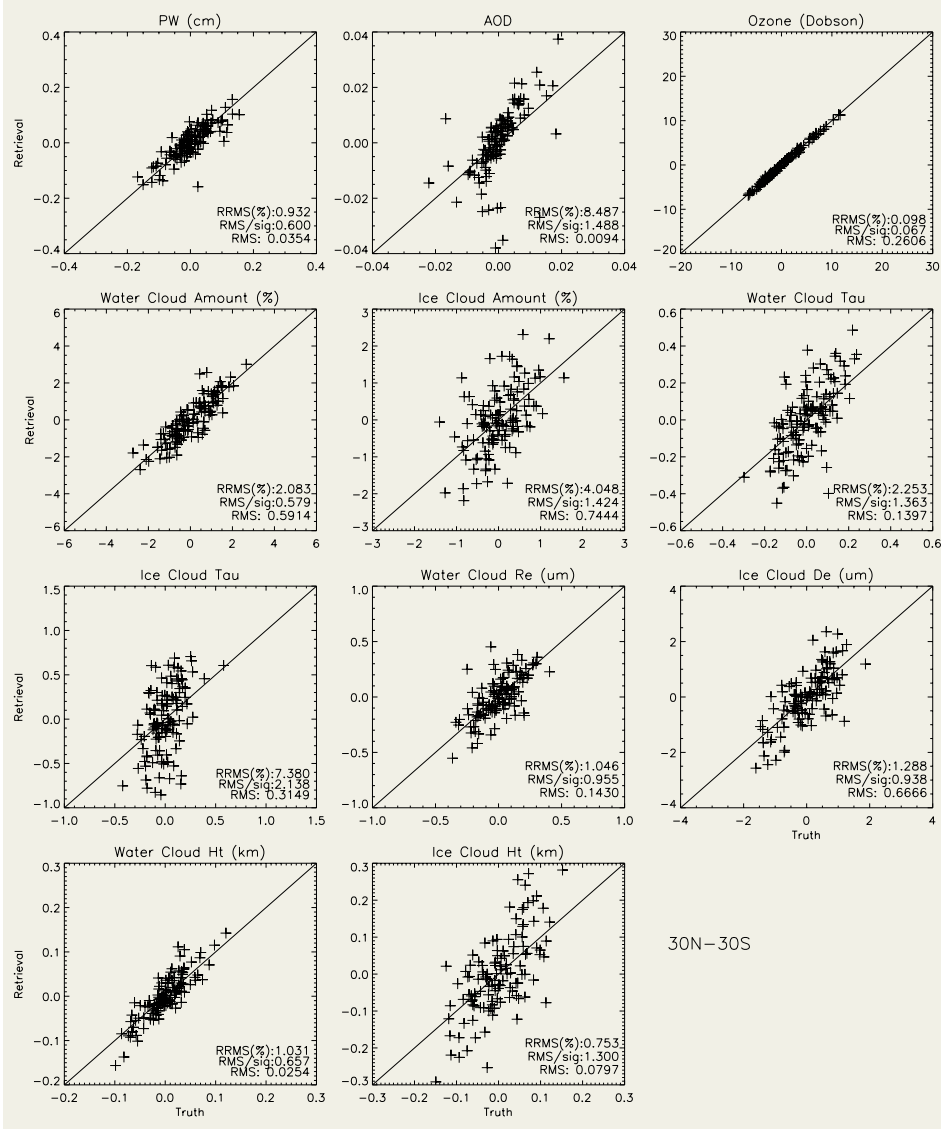
$$\Delta R \neq \sum_i \Delta R_i = \sum_i K \Delta x_i$$



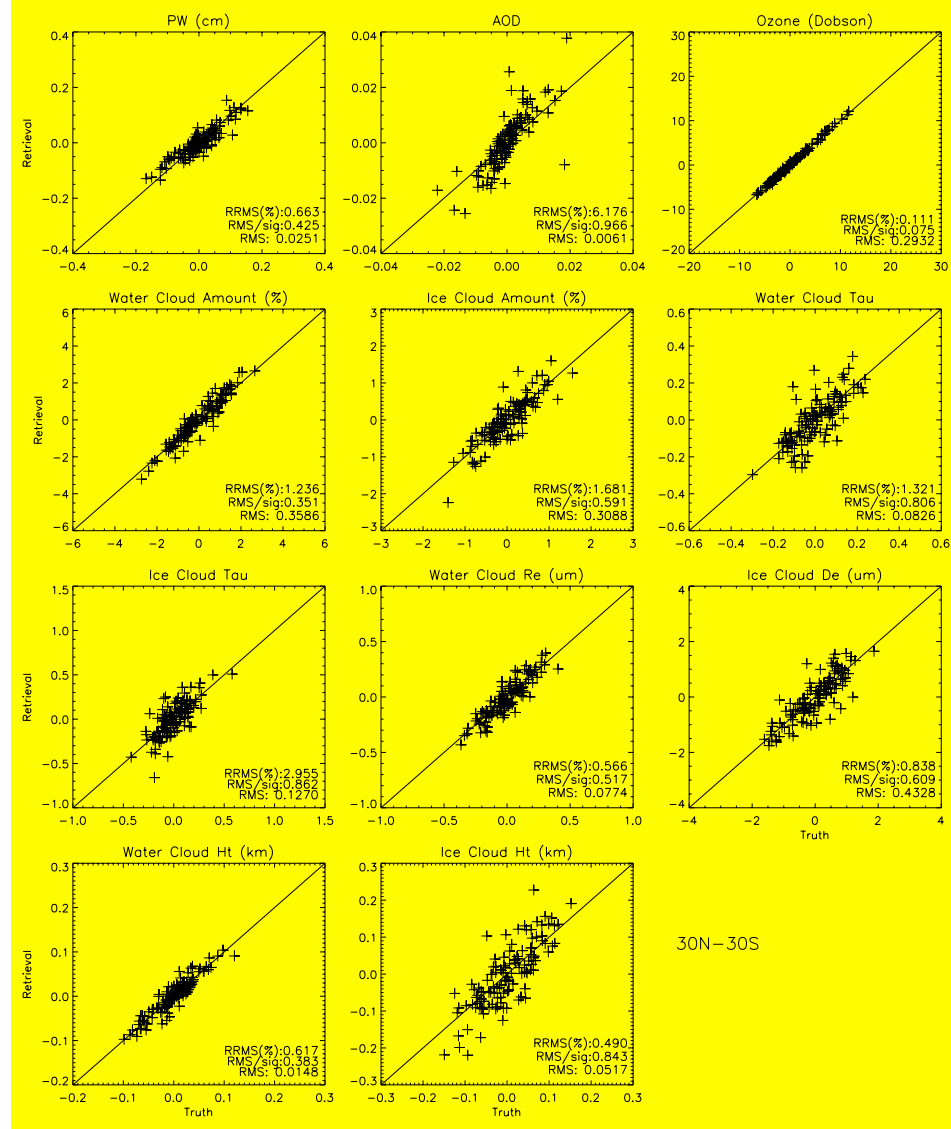


Without nonlinear errors considered

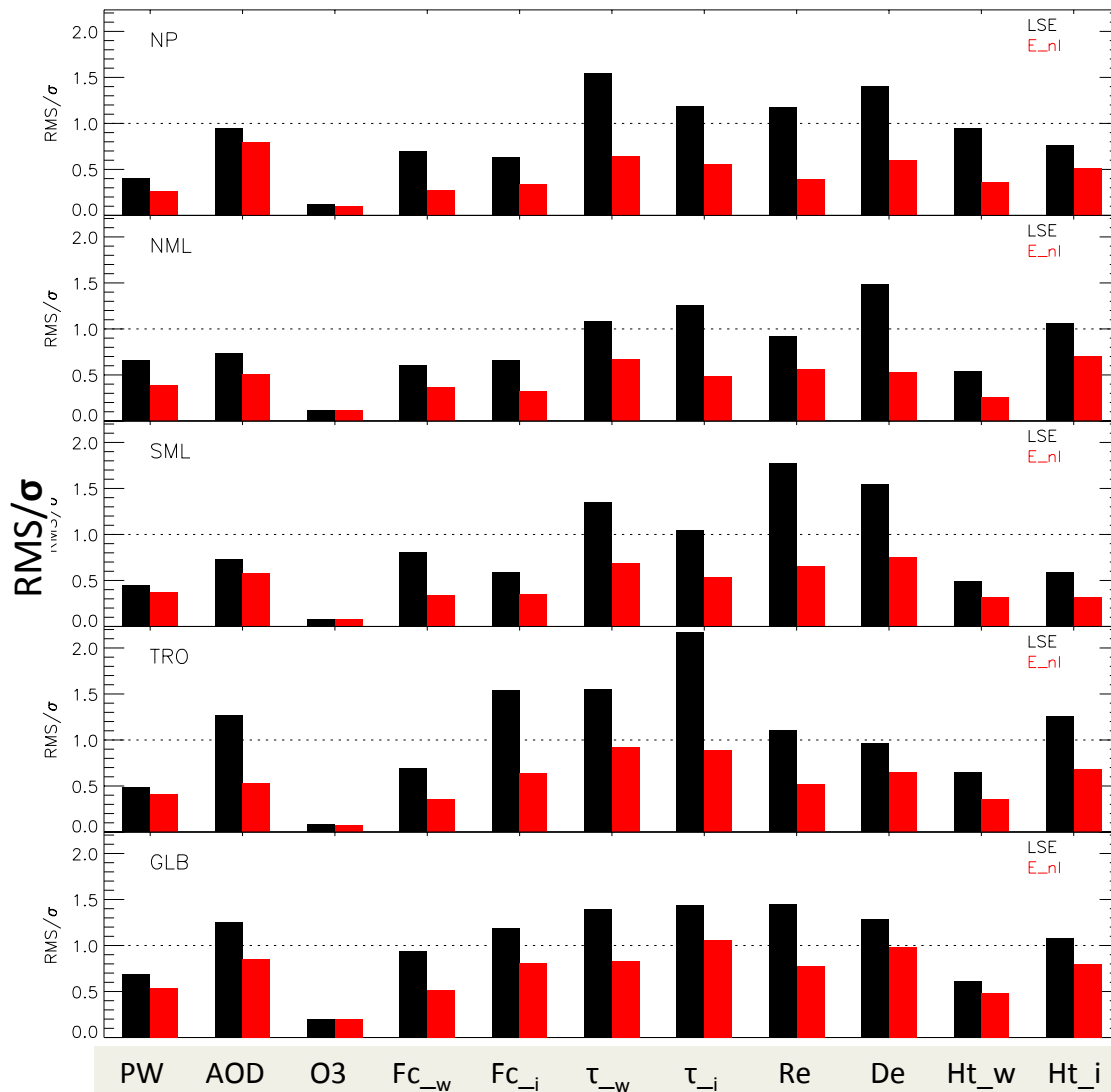
With nonlinear errors considered



Without nonlinear errors considered



With nonlinear errors considered



**RMS comparison in all regions
fro all 11 parameters.**

Each panel represents a
different region.

The RMS is normalized by the
variation σ for each parameter.

Without nonlinear error considered (LSE)

With nonlinear error considered (optimal detection)

Conclusion

- ✓ The cloud PDF approach provides a simple, fast, and effective way to simulate the mean spectral reflectance over large time/space scales with a large volume of satellite data.
- ✓ Using ten years of satellite data and the PDF method, we tested the concept of using fingerprinting approach for climate change detection/attribution.
- ✓ Comparing the fingerprinting retrieval to the observational truth, the RMS differences are less than 2σ of the variance for all variables in all regions. A large error usually corresponds to the variables with large nonlinear radiative response, such as cloud τ and ice particle size.
- ✓ Using the optimal detection method to take into account the nonlinear radiative error in the kernels, the retrieval accuracy is significantly higher, so that the RMS errors are reduced to less than 1σ of the variance, indicating the profound impact of the nonlinear error on fingerprinting retrieval.
- ✓ Ozone retrieval has the highest accuracy among all variables in all cases.
- ✓ The test results demonstrate that the concept of climate change fingerprinting based on the reflected solar benchmark spectra is viable.